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# Fusing Stretchable Sensing Technology with Machine Learning for Human–Machine Interfaces

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## Abstract

Skin is the largest organ with the functionalities of protection, regulation and sensation. The emulation of human skin via flexible and stretchable electronics generates electronic skin (e-skin), which has realized artificial sensations and other new functions that cannot be achieved by conventional electronics, such as stretchability and self-healing. Currently, most e-skin systems focus on data acquisition and transmission, however the implementation of perception within systems, *i.e.* sensory data processing, is still in its infancy. Integrating the perception functionality into a flexible and stretchable sensing system, namely artificial skin perception, is critical to endow current e-skin systems with much higher intelligence. Here, recent progresses in the design and fabrication of artificial skin perception devices and systems are summarized, as well as challenges and prospects are discussed. The strategies for implementing artificial skin perception utilize either conventional silicon-based circuits or novel flexible computing devices such as memristive devices and synaptic transistors, which enable artificial skin to surpass the human skin with a distributed, low-latency and energy-efficient information processing ability. In future, artificial skin perception would be a new enabling technology to construct next-generation intelligent electronic devices and systems,

which paves the way for advanced soft robotic applications, such as surgical assistance, rehabilitation, and prosthetics.

## 1. Introduction

Skin, the largest organ with an entire area of ~2 m$^2$ in human body, protects us from external environments, regulates homeostasis including body temperature, and mediates the sense of touch.[1-4] It houses a huge nerve network comprising a variety of sensory receptors, widely distributed within epidermis, dermis, and hypodermis layers (**Figure 1**a). These sensory receptors are responsible for detecting various internal and external disturbances, such as pressure, strain, vibration, temperature, pain, and chemical species, allowing humans to perceive and interact with the world. This inspired scientists and engineers to develop flexible and stretchable electronic devices or systems to emulate the functionality of the human skin, known as electronic skin (e-skin). Recently, tremendous efforts have been made in developing e-skin, from materials innovation to structure designs, which concentrate on the improvement of sensing capability (*i.e.* stretchability, sensitivity, long-term monitoring, etc.), data transmission, and the realization of new functions such as self-healing.[5-7] However, as one of the essential elements to mimic human intelligence, the functionality of perception, *i.e.* interpretation of acquired sensory data, still in its infancy in most current e-skin systems. Implementing the perception functionality on a flexible or stretchable sensing system, referred to as artificial skin perception is vital to realizing an authentically intelligent artificial skin, with capabilities beyond human skin (Figure 1b). Coupled with sensing, feedback and other technologies (Figure 1c), artificial skin perception will significantly accelerate the development of next-generation soft robotics, where a low-latency and energy-efficient data processing module is required to enable fast adaptation to dynamic environments.

Currently, perception processes of most e-skin systems take place in centralized processing units, *i.e.* computers or servers in the cloud, located far away from the sensing systems where sensory signals are generated. These sensory signals, usually time-serial, unstructured, and redundant, need to be continually sent to an external processing end. As a result, there will be a tremendous volume of data movements between the sensing end and the processing end, leading to huge energy consumption.[8, 9] Moreover, the frequent and continuing data exchange causes a serious burden to data communication due to the limited bandwidth of communication channels in current sensing systems, especially when a great number of sensors are mounted on the large-area sensing systems.[9-11] This leads to a notorious latency problem, *i.e.* a time delay in response for the data communication.[9] Such latency issue severely hinders the development of ultra-fast responsive and delay-sensitive intelligent systems, such as advanced robotics and prosthetics. Artificial skin perception is aimed to overcome these critical issues.

In conventional silicon-based electronics, edge computing brings computation closer to the place where data is produced. Hence, edge computing can alleviate the issues of limited bandwidth and high energy consumption, which has been considered as an effective computing paradigm for delay-sensitive tasks, such as interactive robotics and the Internet of Things (IoT). When edge computing technology meets flexible and stretchable electronics, artificial skin perception is becoming increasingly possible. Analogous to edge computing, artificial skin perception moves all or part of the sensory data processing from external centralized processing units to the flexible and stretchable sensing systems. The sensory data processing can be implemented by the sensors themselves or localized processing units close to the sensors. In this way, a low-latency and energy-efficient information processing can be achieved in the decentralized artificial skin perception. However, it is challenging to incorporate the sensory information processing into a flexible and stretchable system, as a result of current flexible integration techniques and computing technology. With recent progress in materials science, manufacturing processes, and electronic device miniaturization, ultra-thin chip technique and flexible hybrid electronics are successively developed, which render conventional complementary metal-oxide-semiconductor (CMOS) based processing units suitable for artificial skin perception. In the former, silicon (Si) wafers would lose their rigidity when being thinned down to ~150 μm and become more flexible with a smaller thickness.[12-14] In the latter, rigid CMOS-based circuit components for computation and communication, and soft elements for sensing are harmonically integrated into a hybrid system, which are interconnected by flexible or stretchable wires.[15-23] Such integrated approach enables the hybrid system to possess both the good mechanical properties of flexible and stretchable electronics, and the superior functionality with high reliability of CMOS-based electronics. Alternatively, artificial skin perception can be achieved by using novel flexible and stretchable computing units such as memristive devices,[24-28] and synaptic transistors.[29-32] Great efforts are made recently in novel computing devices and systems, which have been employed to implement not only general-purpose computing such as Boolean logic and analogue matrix-vector multiplication[33-36], but also advanced brain-inspired neuromorphic computing[30, 37-44]. Unlike traditional CMOS-based electronics, these new computing devices can be fabricated in a mild, low-cost, and large-scale way that is compatible with flexible and stretchable electronics[25-27, 30], enabling a homogeneous integration with soft sensing elements. To address the key requirements and challenges of artificial skin perception arising from new manufacturing process and emerging devices, it is urgent to review the recent progress in the interdisciplinary fields.

In this regard, this Progress Report outlines recent advances in artificial skin perception, a new enabling technology for future intelligent systems like soft robotics, from the perspectives of both emerging processes and devices. We firstly present the fundamentals of sensory information processing in human body, involving sensing, transmission, perception, and action, as the neurophysiologic basis of artificial skin perception. Artificial skin perception is then discussed in terms of new manufacturing processes and energy-efficient computing devices, including perception based on commercial CMOS processing units, perception based on flexible memristive devices, and perception based on flexible synaptic transistors. The existing challenges that hinder the development of artificial skin perception are also discussed. In the end, we envision the future prospects of artificial skin perception, in the hope of promoting the development of artificial skin for advanced prosthetics and soft robotics.

## 2. Neurophysiologic basis of artificial skin perception

Sensory information processing in human is controlled by sensory nervous systems that detect and encode stimuli, send sensory signals to the central nervous system, and then interpret the sensory information for feedback actions (**Figure 2**a). Accordingly, there are four main parts in the sensory nervous system, comprising: 1) sensory neurons consisting of various sensory receptors, 2) neural pathways for signal transmission, 3) parts of the brain involved in sensory perception, 4) muscle activation as feedbacks. The corresponding processes are simply referred to as sensing, transmission, perception and action, which are also the basis of the robotic sensing systems (Figure 2b).

Skin is the most important organ for sensing, which comprises a variety of sensory receptors from the epidermis layer to the hypodermis layer.[45] These receptors are generally classified into four categories, namely mechanoreceptors, thermoreceptors, nociceptors, and proprioceptors. Mechanoreceptors are sensory neurons or peripheral afferents that are responsible for mechanical stimuli, such as pressure, touch, stretching, and vibration. There are toally about 45 thousands mechanoreceptors within the skin,[46] which comprise Meissner’s Corpuscles, Merkel Disks, Ruffini Organs and Pacinian Corpuscles (Figure 1a). Mechanoreceptors are classified into fast adapting (FA) units and slow adapting (SA) units by adaptive response time.[45, 47] FA units respond rapidly and immediately after skin deformation, while SA units show continuous response to sustained deformations. According to the receptive field, both FA and SA units are further categorized into two types: I) small receptive fields with sharp borders, and II) large receptors with indistinct borders. Specifications of these mechanoreceptors, such as adaptation rate, receptive field area, location, effective stimuli, and function, are summarized in **Table 1**.[45, 47, 48]

Thermoreceptors are a category of sensory neurons that respond to temperature change. They do not measure absolute temperatures, but temperatures relative to the temperature of human body. The sensitivity of temperature response depends on the surface area perceiving the change in temperature, and the best is about 0.3 °C. There are two kinds of thermoreceptors in the skin, namely cold receptors and warm receptors, which have different response ranges in skin temperature.[49] Nociceptors, also referred to as pain receptor, are used to detect the noxious stimuli that would or potentially give rise to tissue damages. In skin, nociceptors comprise four types of functional receptors: high threshold mechanonociceptors or specific nociceptors, thermal nociceptors, chemical nociceptors, and polymodal nociceptors. The first three types of nociceptors are specialized for detecting intense mechanical stimuli (*i.e.* pinching, cutting, stretching, etc.), intense thermal stimuli (extremely high or low temperatures), and intense chemical stimuli, respectively. The last type, polymodal nociceptors, can respond to various intense stimuli including mechanical, thermal and chemical ones. Proprioceptors are sensory receptors responsible for a category of conscious sensations, including the senses of limb position and movement, the sense of balance, the sense of force, the sense of effort, and the sense of heaviness. In most cases, these senses are not generated by individual receptors, but by populations of proprioceptors that are distributed in skin, muscles, tendons, and joints[50]. The brain can further integrate the proprioceptive senses with other sensory information such as visual, audio, vestibular or olfactory senses to create an overall representation of body position and movement.

For artificial skin, the first step is to obtain reliable detected signals analogous to the functionality of sensory receptors, which is the basis of the sensory perception. To achieve this, artificial skin materials and devices should be highly flexible, even stretchable, tough and sometimes self-healing. Significant progress has been made recently in developing various flexible or stretchable sensing devices from the prospective of materials innovation and structural designs, which are listed in **Table 2** (according to the type of sensory receptors).[51-

117] For more details, readers may refer to the following recent review articles.[5, 6, 15, 118, 119]

After receiving a stimulus, the sensory receptor converts the sensory signal from the stimulus to an electrical signal that transmits in the peripheral nervous system (PNS) and central nervous system (CNS). Specifically, the membrane potential of a sensory receptor varies with the strength and duration of a stimulus that affects the ion channels in the membrane. Once the membrane potential reaches a threshold, the neuron will fire or generate an action potential. The action potential generated in PNS is transmitted to the spinal cord via sensory nerve pathways, and in most cases, is sent to the brain for perception.

After the process of neural signal transduction, sensory perception occurs in the brain. The brain is the processing center of perception in human, which is highly centralized and responsible for high-level and comprehensive perceptual activities such as cognition, planning, and intuition. However, several low-level perceptual activities such as reflexes and muscle activation, could be directly processed by the PNS.[120] In other words, the sensory signals do not need to be sent into the brain, and a perceptual decision will be immediately made once the sensory signal reaches the spinal cord (Figure 2a). Compared to the brain, the processing way of the low-level perceptual activities in the PNS is decentralized, distributed and localized. Localized processing not only enables a rapid response to external stimuli for survival, but also can alleviate the computing burden in the brain,[121] and so it has been used in interactive robotics.[120] In addition, recent neuroscience studies have demonstrated that some sensory receptors can also perform specialized computations before sending signals downstream; this is termed on-receptor computing.[10, 122] These neurophysiological evidences further highlight the importance of placing perception functionality on or near sensing modules within a flexible or stretchable system (Figure 2b), which also provides a bioinspired approach to develop artificial skin perception devices and systems.

In most cases, a decision-making command after the sensory signal is processed by the brain and other processing organs will be sent to muscles or glands in the form of action potentials. Decision-making information is encrypted in these action potentials and usually used for motion and status control, which can be regarded as the active feedback in response to the stimuli. This process is referred to as the process of action.

## 3. Artificial skin perception

Recent advances in materials science, manufacturing processes, electronic device miniaturization, and computing architectures, enable artificial skin perception to become possible. In this section, we summarize recent significant progress in artificial skin perception based on the type of local computing units – CMOS-based computing components and novel flexible or stretchable computing elements including memristive device and synaptic transistor. Requirements and challenges for each strategy are discussed, which will shine some light on artificial skin perception for the future.

### 3.1 Artificial skin perception based on CMOS devices

The most straightforward strategy to realize artificial skin perception is placing commercial CMOS-based computing units into the flexible or stretchable system. Beside computing units, other functional modules, such as modulation circuits, conversion circuits, and communications, are also required for the construction of a complete artificial skin system. The computation and other functional modules are typically rigid and brittle, so it is challenging to interface them with the flexible or stretchable system.

To solve this issue, one approach is to directly decrease the thickness of Si wafer to make it flexible, named as ultra-thin chip. When a system is physically built on the ultra-thin chip (typically $< 50$ μm) substrate, the system will become flexible and bendable.[14, 123] Such ultra-thin chips can be obtained by wafer thinning from a bulk Si substrate (**Figure 3**a) or exfoliation from a silicon-on-insulator (SOI) substrate (Figure 3b). The manufacturing processes for ultra-thin chips generally involve techniques like polishing, grinding, thinning-by-dicing, die assembly, interconnection, etching, transfer, and packaging.[12, 124-128] The ultra-thin chip technique can be employed to fabricate various functional components including sensing elements, perception units, driving circuits, power supply and data transmission modules, and has been applied in robotics, wearable devices, healthcare, and Internet of Things.[14, 127-129] Coupling with structural design strategies, *i.e.* wave/wrinkle pattern, stretchable systems based on ultra-thin chips can be achieved.[125] The ultra-thin chip technique paves one possible way to building up the intelligent artificial skin systems with both sensing and perception functionalities. However, there remain several challenging issues to be solved before commercialization, such as packaging, residual stress, stress analysis model, and strain effect on electrical performance. Unlike conventional chips, ultra-thin chips cannot be bonded easily by wire-bonder because a large impulsive force from the bonder tip may destroy the thin fragile wafers. Bumps coarsening and possible electrical discontinuity in/out of plane also increase the complexity of the ultra-thin chip packaging, especially for three dimensional (3D) integrated circuits. In addition, much effort is needed to investigate the stress-induced side effects and further build up accurate stress-performance models to guide the design of ultra-thin chips.

Flexible hybrid integration is another effective way to implement artificial skin perception by using commercial devices. Commercial rigid functional components are directly interfaced with soft elements such as sensors and interconnection wires, to construct a flexible (Figure 3c) or stretchable (Figure 3d and 3e) hybrid electronic system.[17, 130] When the hybrid integrated system is bent, twisted, folded, or stretched, soft parts are deformed to accommodate the strain, while rigid counterparts do not deform. To meet the large deformation requirements, as needed in advanced soft robotics and prosthetics, tremendous efforts have been made via various structural designs in recent years, including serpentine,[131-135] self-similar structure,[136, 137] arc-shaped bridge,[138, 139] helices,[130, 140] origami,[141] and kirigami.[142, 143] Based on the structural designs, a number of stretchable electronic systems have been reported. However, these systems primarily focus on the functions of signal detection and data transmission. In other words, sensory signals in current stretchable systems usually need to be sent to external processing units, *i.e.* portable phones, computers, and clouds, for data analysis, which is different from the paradigm of artificial skin perception.

More recently, a hybrid integrated epidermal electronic system (**Figure 4**) with both the sensing and perception functionalities was reported by Rogers's group.[144] The hybrid system comprises four main functional layers (Figure 4a): 1) an electronic layer for monitoring and processing sensor data, 2) a microfluidic chamber for mechanically isolating the skin and interconnection wires, 3) silicone encapsulation layers, and 4) a magnetic loop antenna for wireless data transmission. The electronic layer consists of various commercial functional components, such as amplifiers, analog filters, LED drivers, power circuits, photodiodes, analog-to-digital converters, microcontroller, and system-on-a-chip, which are bonded by stretchable interconnection wires. Hence, the stretchable epidermal electronic system can perform in-sensor data analytics, *i.e.* recognition of the peaks and valleys of data waveforms, without sending them to external processing units. The block diagram for real-time processing of the ECG waveforms detected by the system is shown in Figure 4b. The sensing and perception results of the system for ECG signals can be comparable to that of a gold standard (Figure 4c). In addition, other vital information of human body such as respiratory rate, heart rate (Figure 4d), blood pressure, and blood oxygenation can also be computed from the raw recorded ECG, photoplethysmogram (PPG) and skin temperature signals.

Despite the promise of commercial devices for artificial skin perception, there remain challenges regarding the reliability and credibility of the system, especially the stability of soft-hard interface. Commercial rigid components and soft elements often show significant differences in stretchability and Young's modulus. Specifically, rigid and hard materials typically show high Young's modulus, e.g. silicon and metal materials with the Young's modulus of ~100 MPa,[6] while soft elements have low Young's modulus, e.g.

polydimethylsiloxane (PDMS) of ~1 MPa, and Ecoflex of ~100 kPa.[15, 145-147] The large mechanical mismatch will lead to stress concentration in the joint area between soft and hard components, which may lead to the failure of the whole system when being bent or stretched. In practical applications, the requirements of artificial skin system in mechanical properties are varied in different application scenarios. For example, to monitor physiological signals on human skin, the system must have a Young's modulus of 0.1–2 MPa and a stretchability of 30–70%, comparable to human epidermis.[15, 148] Coupling with the aforementioned structural designs, proper selection of system materials according to the specific application can alleviate the soft-hard interface issue. For artificial skin perception, another issue is the loss of form factor caused by the addition of bulky commercial rigid components and immature interconnection techniques, which may limit the application in miniaturized and implantable domains.

### 3.2 Artificial skin perception based on flexible memristive devices

Memristive devices are two-terminal electrical switching devices, whose internal resistance states rely on the history of applied voltage or current.[33, 149] Such devices can be employed for information storage and processing.[150] Typical memristive devices include resistive switching memory (RRAM), phase change memory (PCM), magnetic random access memory (MRAM), and ferroelectric random access memory (FRAM). Owing to their simple two-terminal structure, low operating energy, high switching speed, and direct in-memory computing ability, memristive devices have been widely developed for next-generation memory and computing components in the post-Moore's law era.[33, 42, 151-157] Moreover, memristive devices are easy to be fabricated using compatible processes with current flexible or stretchable electronics, such as printing and solution-based methods.[4, 25, 28, 155, 158-166] These merits make memristive devices energy-efficient computing units, which can exceed conventional CMOS-based circuit technology, and are suitable for artificial skin perception.

According to the type of computing paradigm, the applications of flexible memristive devices are classified into two main categories: 1) general-purpose computing, and 2) neuromorphic computing.

### 3.2.1 Flexible memristive devices for general-purpose computing

According to the definition, a memristive device can be configured into different resistance states depending on external operations and its previous internal state. Through delicately regulating the sequences of operations and/or array configuration, flexible memristive device or array can perform general-purpose computing tasks, such as threshold detection, in-memory digital computing, and in-memory analogue computing (**Figure 5**a).

In a memristive device, the resistance changes in response to electrical stimuli can be used as a criterion for threshold detection. For most of RRAM-based memristive devices, the electrical resistive switching phenomenon of the device can be well explained by the mechanism of the formation/rupture of nanoscale conductive filaments, in which the externally driven ion transport plays an important role.[151, 155, 167-170] When an external driving force is below a critical value, the ions cannot move. Only if the external driving force exceeds the critical value, can the ions move. The physical principle can be regarded as a natural threshold evaluation process for processing information. For instance, He et.al. reported a flexible artificial reflex arc system (Figure 5b) that consisted of a pressure sensor for tactile sensing, a non-volatile resistive switching device for perception, and an electrochemical actuator that acted as the muscle in response to tactile stimuli.[121] Only when the tactile stimulus reaches a threshold, the resistive switching device can be activated and trigger the actuator to move. Here, the non-volatile resistive switching device can perform a threshold computing in the flexible system. Due to such decentralized processing way, artificial reflex arc system not only realizes a rapid response to pressure stimuli, but also liberates the centralized processing units from tremendous low-level decision-making activities. Beside the non-volatile resistive switching device, diffusive memristive device where the formed conductive filaments spontaneously break up after removing external applied voltages can better perform threshold computing, due to its natural threshold effect.[43, 167, 171-173] The diffusive device has been used in flexible (Figure 5c) or rigid artificial nociceptor system,[88, 89] and artificial afferent nerves.[174]

On top of simple threshold detection, memristive devices and arrays can perform many complex general-purpose computing tasks via rational operations and array configurations, such as digital Boolean logical computing (Figure 5a), which is aimed to substitute the modern digital computer. Classical Boolean functions, the basis of digital computer, such as AND gates, NOT gates, NOR gates, and NAND gates, have been recently demonstrated based on rigid memristive device arrays.[150, 175-179] Furthermore, one-bit full adders are experimentally verified by rationally assembling the memristive device-based Boolean logic operations.[36] Compared to significant progress in rigid arrays, in-memory digital computing based on flexible memristive devices are rarely reported,[180, 181] mainly due to the unsatisfactory device reliability. Recently, Jang et. al. demonstrated Boolean logics, *i.e.* NOT and NOR gates, using a flexible one-selector–one-memristor (1S1R) array.[181] Multiple logic operations can be simultaneously performed on different rows in the array, which realizes a parallel computing for energy-efficient flexible electronics.

In addition, in-memory analogue computing can also be performed by memristive arrays, because they are inherent to implement matrix–vector multiplications based on the Ohm's law and Kirchhoff's law.[34, 37] The analogue computing operations are specialized to accelerate computationally intensive tasks such as image compression,[182] sparse coding,[183] linear equation solver,[35, 184] and eigenvector solver.[35] The core multiplication operations are explained as follows. When an input vector of voltages is applied to the rows of a memristive array, the summed current along a column is collected, which can be regarded as the dot product of the input voltage vector and the memristive conductance vector of the column

(Figure 5a). Obviously, multiple multiplications can be simultaneously performed through multiple columns in a single computing cycle, enabling a parallel and high-throughput computing paradigm.

In short, in-memory digital and analogue computing based on memristive devices and arrays provides a promising solution for fast and energy-efficient artificial skin perception. However, memristive devices suffer from several challenges such as poor resistance tuning ability, state instability, read-write nonlinearities, excessive cycle-to-cycle and device-to-device variations, and low device yield.[151, 182] These issues will be more serious in artificial skin perception because flexible memristive devices usually exhibit worse performance than rigid counterparts. To the best of our knowledge, there has been no report on analogue computing based on flexible memristive devices or arrays. Hence, much effort is still needed to improve the device performance and fabrication process, especially in flexible devices and arrays, to realize artificial skin perception.

### 3.2.2 Flexible memristive devices for neuromorphic computing

Different from general-purpose computing, neuromorphic computing is a new intelligent technology, which is inspired by the neural structure and operational way of the brain. There are about $10^{12}$ neurons in the brain and neurons are interconnected via synaptic connections (synapses), constructing a huge neural network (**Figure 6**a). The information processing in the brain is executed through the complex neural network that is operated in a massively parallel, distributed, and event-driven way.[185] To take advantage of neuromorphic computing, artificial synapses and neurons are essential, which perform the localized computation and data storage function. Flexible or stretchable memristive devices can be used to emulate the functionality of synapses and neurons, which provides an alternative way to realize artificial skin perception.

A two terminal memristive device is analogous to an artificial synapse connecting a pre-neuron to a post-neuron, of which the resistance state represents synaptic weights (Figure 6a). Synaptic weights can be strengthened or weakened over time in response to the synaptic activity, referred to as synaptic plasticity, which is believed to underlie the learning and memory of human beings. Recently, tremendous effort has been made in emulating artificial synapses by using various flexible (Figure 6b) or stretchable memristive device.[25-28, 186-193] Typical synaptic dynamic properties (Figure 6c), such as excitatory postsynaptic current (EPSC), short-term plasticity (STP), long-term depression (LTD), long-term potentiation (LTP), paired pulse facilitation (PPF), and spike timing dependent plasticity (STDP), have been widely explored in flexible memristive systems, which demonstrates the feasibility of memristive device-based synapses for neuromorphic computing. For instance, an electrical synapse with as high as 600 continuous conductance states has been achieved recently by using a flexible organic PEDOT:PSS-based memristive device, benefiting the continuously tuned ability of artificial synapse.[186] LTP, STP, PPF, and STDP synaptic properties were mimicked in the device, which could also sustain the folded tests. To render it suitable for harsh environments such as twisting and stretching, as required in soft robotics, stretchable memristive device-based synapses are consequently developed. By rationally selecting Ag nanoparticle-doped composite materials with good stretchability and low Young’s modulus, the fabricated artificial synapse can be stretched up to 60% strain while maintaining its synaptic functions.[187] In addition, the device implemented the process of “learning–forgetting–relearning”, even in a stretched state of 35% strain.

As another critical element for implementing the neuromorphic computing, artificial neuron can be emulated by using memristive devices as well. Compared to synapses, the emulation of neuron is very difficult because a neuron must at least perform two complex processes of “integration” and “fire”, in which a neuron can integrate information over a long time period and trigger action potentials above a critical value. Currently, most of memristive device-based artificial neurons are realized by coupling with additional commercial components, such as spike event generator.[194-196] Fortunately, Wang et. al. recently developed a hybrid neuro-transistor system that can emulate the neural functions at lower static power, which offers an alternative physical embodiment to build up a complete neural network.[197] However, to our knowledge, there is no report about flexible memristive device-based artificial neurons.

To perform complex computation tasks, flexible or stretchable memristive arrays are required. A crossbar array of memristive devices is analogous to a synaptic layer that connects the pre-neuron layer and the post-neuron layer, and multiple layers of memristive devices represent a multilayer artificial neural network (ANN) (Figure 6d). According to the encode information, ANN can be generally classified into conventional ANN with static input coding and spiking neural network (SNN) with relative spike timing coding. To date, several groups have adapted the array simulation based on flexible artificial synapses for recognition tasks, which can accelerate some intensive computation tasks. However, the unsatisfactory device performance is still a big challenge for flexible memristive device-based neuromorphic computing, like in analogue computing. In addition, neuron emulation using physical embodiments needs to be extensively explored. There will be a very long way to achieve a practical neuromorphic computing using flexible or stretchable memristive devices, but it opens a novel direction towards artificial skin perception.

### 3.3 Artificial skin perception based on flexible synaptic transistors

Flexible transistor is another physical embodiment for the synaptic emulation, which can execute artificial skin perception. In a three-terminal transistor, the voltage or current pulse is traditionally applied on the gate electrode as a presynaptic stimulus from a pre-neuron, and the channel conductance of the transistor is regarded as the synaptic weight (**Figure 7**a).[198] Compared with memristive devices that often exhibit the uncontrolled resistance tuning behavior due to the stochastic formation/rupture of conductive filaments, three-terminal transistors can easily obtain continuous channel conductance states by gate control, which enables synaptic transistors to be a promising candidate for artificial synapse. A variety of synaptic transistors that exhibit various operational mechanisms such as electrochemical doping,[29, 41, 198-204] charge-trapping,[205-207] and light-assisted reaction,[208] has been continually developed for synaptic emulation and related computation tasks. Here, we focus on recent progress in flexible synaptic transistor-based devices and systems which have been or can potentially be executed for artificial skin perception.

### 3.3.1 Flexible synaptic transistors for neuromorphic computing

To effectively execute neuromorphic computing algorithms, flexible synaptic transistors should be capable of emulating synaptic functionality with high energy efficiency. Recently, great efforts have been made to develop such flexible synaptic transistors, in which the fundamental synaptic properties such as EPSC, STP, LTD, LTP, PPF, and STDP learning rule, have been extensively verified.[29, 199, 209-214] For instance, a low-power flexible synaptic transistor has been reported based on an organic core-sheath nanowire, which can emulate the morphology and working principles of the nerve fiber.[215] In the synaptic transistor, each synaptic event consumed only around 1.23 fJ energy, which is comparable to biological synapses (~10 fJ per synaptic event). In most of synaptic transistors, the retention time of conductance states is very short, ranging from seconds to hours, which limits their practical application in long-term invariant tasks such as pattern recognition and classification. By modifying or doping organic polymers, the retention time in synaptic transistors can be increased.[29, 201] van de Burgt et. al. demonstrated a flexible organic electrochemical synaptic transistor (Figure 7b), in which long-term data retention with more than one day was achieved due to the battery-like switching behavior.[29, 216] The synaptic transistor also displayed a number of discrete conductance states with extremely low noise in a small voltage range (< 1 V). In addition, the device is compatible with low-cost and large-scale flexible fabrication processes, which enables seamless integration of on-skin neuromorphic computing and learning in soft robotics and implantable prosthetics.

For practical applications such as classification and recognition tasks, large-scale synaptic transistor arrays are required. Taking handwritten digit recognition as an example, each image pixel of the handwritten digit after encoding is connected to a pre-neuron in the input layer, and synaptic transistors are located at the junctions between the input and output neurons.[217] As shown in Figure 7d, a presynaptic spike fired from one input neuron simultaneously acts on multiple columns, enabling a highly parallel computing way. Based on such configuration, Kim *et.al.* demonstrated a flexible, lightweight, and disposable neuromorphic system for handwritten digit classification.[218] Simulation results demonstrated a recognition rate of about 70% based on the flexible neuromorphic system (Figure 7e). To date, the flexible synaptic transistor-based neuromorphic computing is still in infancy and there is no experimental demonstration due to the difficulty in the fabrication of the larger-scale flexible synaptic transistor array. In addition, challenges remain in device downscaling and improving switching speed in order to realize a low-latency and energy-efficient artificial skin perception.

### 3.3.2 Flexible synaptic transistors for artificial skin systems

As mentioned in Introduction, to enable artificial skin, flexible intelligent systems with integrated sensing and perception functionalities are highly desired. Owing to the capabilities of synaptic computing and compatible integration, flexible synaptic transistors are good on-skin perception candidates for the development of intelligent e-skin systems. Next, we will discuss recent progress about flexible synaptic transistors-based skin perception in integrated artificial skin systems.

The pioneer research on such integrated system is the demonstration of a dual-organic-transistor-based tactile perception system reported by Zhu and co-workers.[219] In the system, one suspended-gate OFET was used as the pressure-sensing mechanoreceptors for transducing dynamic tactile information into electrical signals, and another synaptic OFET acted as a localized perception element for processing the received electrical signals to gather cognitive tactile information (**Figure 8**a). By virtue of the short-term synaptic plasticity, pressure stimuli with varied intensity, frequency and duration caused distinct postsynaptic currents in the synaptic OFET, due to the accumulation of holes at the chitosan/organic semiconductor interface. The postsynaptic currents read from the EPSCs represent the cognitive tactile information after computing, *i.e.* touch speed, which is different from that obtained from the sensing device alone. More importantly, two OFET devices were seamlessly integrated through fully compatible fabrication processes that are also suitable for flexible electronics. However, as the authors mentioned, quantitative extraction of the dynamic tactile information, such as touch pressure, duration, and frequency, is very challenging in this system, due to the coupling effect of multiple tactile signals. Great efforts should be devoted into the signal coupling and decoupling analysis for such application scenario.

In addition, a neuromorphic tactile processing system with perceptual learning function was developed, which comprised a resistive pressure unit, an ionic conducting polyvinyl alcohol (PVA) cable for signal transmitting and a flexible indium-tungsten-oxide-based synaptic transistor (Figure 8b).[220] The pressure sensing unit and synaptic transistor are separated by the soft ionic cable, which could suppress the signal interferences between these two elements and endowed the system with flexibility. Similarly, the system utilized the short-term synaptic plasticity of the synaptic transistor to process dynamical pressure stimuli for extracting their spatiotemporal correlated feature. The extracted features could be further classified by using machine learning models to realize recognition capability, such as pattern recognition. The system possesses the ability of on-skin feature extraction, which could be integrated into robotics and prosthetics for intelligent artificial skin. However, the features extracted from the system are usually unstructured and user-dependent possibly due to the variations of device or touch process.

To further improve the mechanical flexibility of systems for soft robotic applications, synaptic transistors for processing sensory signals should be stretchable. A stretchable synaptic transistor can be obtained by unconventional fabrication processes, such as spray-coating, printing, or transfer, which has been implemented in a bioinspired neuromuscular system (Figure 8c).[221] In the system, the single-wall CNT-based stretchable synaptic transistor was used to modulate the optical stimuli and generated the electrical postsynaptic signals to activate an artificial muscle actuator, which mimicked the biological sensory and motor functions. Combining with optics, electronics, and biological technology, the neuromuscular system enables an optical wireless communication method, which is promising for the development of next-generation soft robotics, neurorobotics, and prosthetics. It should not be neglected that the complete functional implementation of the system relied on a rigid silicon-based transimpedance circuit that converted postsynaptic currents to appropriate voltages.

In biological neural systems, neurons interact with each other in the spike (action potential) code, which is quite different from the coding scheme (direct coupling of current/voltage signals) in the aforementioned intelligent artificial skin systems. The spike code enables computing in human brain to be event-driven, distributed, parallel, and power efficient. To fully take advantage of the brain computing for skin perception, the first step is to covert the external stimuli information into spikes like those exchanged in neural systems. By virtue of organic electronics technology, flexible functional circuits such as ring oscillators are used to implement the signal conversion in artificial skin systems[222, 223]. Combining with a pressure sensor and a synaptic transistor, researchers developed a flexible organic artificial afferent nerve (Figure 8d) that can collect pressure information, convert the external stimulus into spikes, and then perform synaptic computing to infer the underlying information.[223] The system realized a simple spike-based information processing way, but it inspires the feasibility of the SNN that is usually used to implement complex perception tasks such as speech recognition, emotion understanding, global decision, and consciousness. Moreover, the hybrid system can be directly used to stimulate a biological neuron, which enables flexible electronic devices to restore muscular activation or to substitute for human tissues or organs.

## 4. Summary and Perspectives

The past few years have witnessed tremendous efforts in areas of flexible and stretchable electronics involving new manufacturing processes and innovative electronic computing devices (**Figure 9**), which enable a promising attempt to implement artificial skin perception. Unlike conventional data-centralized processing approach, artificial skin perception has the ability of processing sensory data within a flexible and stretchable sensing end, leading to a low-latency and energy-efficient system response. In this Progress Report, we discussed the recent progress in artificial skin perception, which involves the state-of-art computing units from commercial CMOS-based elements to novel flexible electronic devices. New manufacturing process techniques, such as ultra-thin chips and flexible hybrid electronics, can utilize the off-the-shelf computing components to implement the perception function in a flexible and stretchable system. Researchers have recently demonstrated such intelligent systems for advanced healthcare and gaming control.[224] Emerging flexible computing devices, such as memristive devices and synaptic transistors, can perform massively parallel, fast and energy-efficient information processing. It is promising to integrate them into current flexible and stretchable systems to implement general computing or neuromorphic computing for sensory perception. Nevertheless, artificial skin perception is still in its infancy, in particular for emerging computing devices-based perception. Challenges remain in several respects such as limited computing ability, immature system-level integration, and the loss of form factor, which are discussed in detail below.

(1) Limited computing capability. Current artificial skin systems with the perception functionality are limited to solving relatively simple computation tasks such as threshold evaluation and peak detection, which is far away from the requirements of real applications like materials recognition, pose estimation, shape perception, and *in-situ* analysis. For CMOS devices-based artificial skin perception, integrating more functional components into flexible or elastic materials is a direct way to increase the computing capability of the system. However, for advanced intelligent algorithms like deep learning, they are still challenging to be deployed in the flexible and stretchable systems, because there are millions of internal parameters need to be simultaneously stored and adjusted during running procedures.[225-227] Recently, edge artificial intelligence (AI) chip technology, referring to running AI processing on a standalone device, enables the miniaturization of AI-capable processors. Several prototypes of edge AI chips, such as Arm Cortex-M55, Ethos-U55, and tensor processing unit (TPU), have been successfully developed by companies like ARM, Apple, Intel and Google. The edge AI chips offer a possibility to realize a much stronger and more powerful artificial skin perception with the help of flexible hybrid integration. For emerging computing devices-based artificial skin perception, there is still a long way for real application since most of physical devices can only perform a single or several-step computations, far from enough for a complete function. Depending on the specific application, developing an artificial skin system where only simple computation steps are required might be an effective way to utilize the emerging computing devices at the current stage. Bioinspired systems can provide some valuable guides towards this direction.

(2) System-level integration. Seamless integration in system level is challenging for artificial skin perception, partly because it involves multidisciplinary domains such as materials, mechanics, electrical engineering, and computing science. For the promising hybrid integrated systems, despite that many efforts have been made recently, soft-hard interface

issue is still one of the biggest barriers before its commercialization. A variety of fabrication process techniques and structural design strategies has been adapted to improve the stretchability and reliability of the system. However, there is lack of a universal standard that is used to define critical process steps and layout parameters, such as interconnection structures, line widths, unit-to-unit connectors, and layer-to-layer connections, like conventional CMOS technology. Moreover, simulation tools for predicting the performance of an integrated system as a function of mechanical strain should be explored. For the artificial skin perception systems without hybrid technology, a compatible process that allows monolithically integrating both soft sensing elements and high-performance computing units into a flexible and stretchable substrate is very challenging. Printed electronics possess the capability to create such artificial skin systems, but their computing ability is limited due to the low or moderate device performance of current organic electronics. Furthermore, to achieve a CMOS components-free stretchable artificial skin system, intrinsically stretchable materials, devices and systems, in their early infancy, deserve more attention.[228, 229]

(3) Loss of form factor. Compared to current e-skin systems, a great number of circuit modules such as computing components, memory units, and relevant peripheral circuits, need to be integrated into an artificial skin perception system. The functional parts and their interconnection with other soft elements will significantly increase the volume of the whole system, leading to the loss of form factor that goes against the miniaturized and low-cost fabrication principle. In addition, it may cause discomfort to users and is not aesthetically pleasant, especially in the case of a large-area perception system where a great many of sensors and computing units are required.

Apart from these challenges, some other issues such as reliable sensing, wireless communication, and power supply, should be overcome for practical application of artificial skin perception systems. Precise and reliable sensing is the foundation of sensory perception, for which readers may refer to the recent review articles.[230, 231] As to wireless communication, the volume of data that needs to be sent to external computers or cloud end will decrease in an artificial skin perception system, because most of sensory data are locally processed in system and only little data need to be sent out for further analysis or storage. It therefore reduces the burden of data transmission compared with current e-skin systems, but challenges remain. Power consumption will become another priority concern in the design of artificial skin perception systems. Different from e-skin systems, a large proportion of system power consumption in artificial skin perception systems will be shifted from data transmission to data computing. Hence, designing power supply solutions requires a careful consideration on the data storage, computing, and communication architecture. In the end, we hope artificial skin perception would provide a new computing paradigm for future flexible and stretchable systems, paving the way towards an authentically intelligent artificial skin for the applications of advanced wearable devices, adaptive prosthetics, and interactive robotics.

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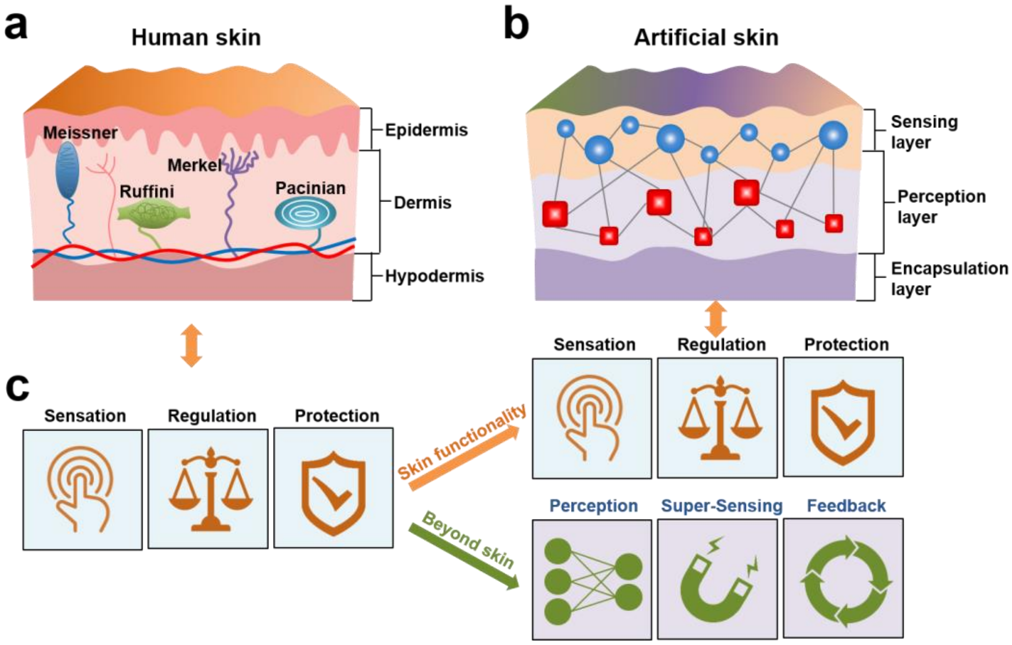

**Figure 1.** Schematic of human skin and artificial skin. a) Human skin consisting of the epidermis, dermis, and hypodermis layers. b) Artificial skin consisting of the sensing, perception, and encapsulation layers. c) The functionality of human skin and artificial skin. Artificial skin not only executes the human skin functionalities such as sensation, protection, and regulation, but also goes beyond the human skin with the localized perception, super-sensing, and active feedback.

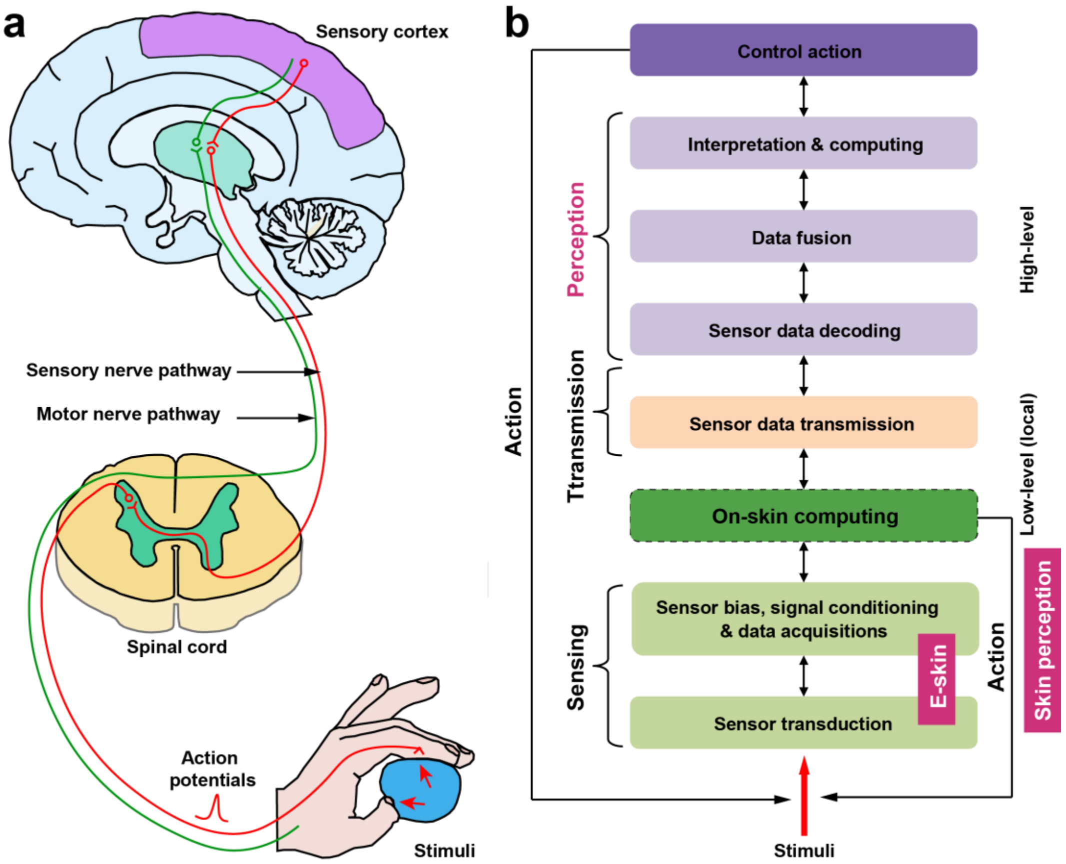

**Figure 2.** Sensory information processing process in the human and electronic systems. a) Neurophysiologic basis of sensory system for sensing and perception. b) Hierarchical functional block diagrams of information processing in modern electronic systems.

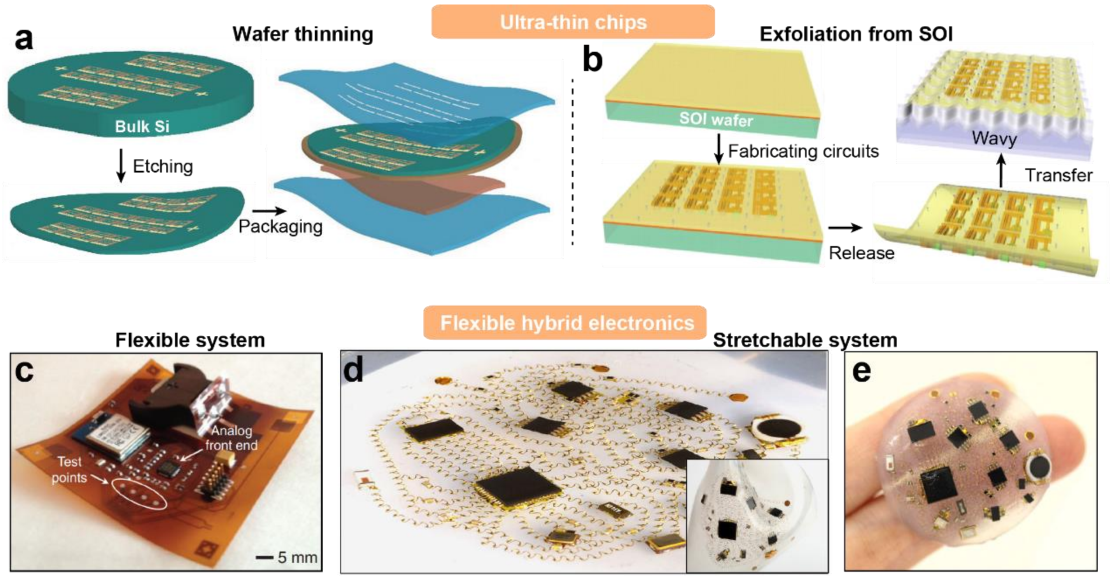

**Figure 3.** Artificial skin perception based on CMOS electronic devices involving ultra-thin chips and flexible hybrid electronic techniques. a) Ultra-thin chips obtained by wafer thinning from a bulk silicon (Si) substrate. Reproduced with permission.[12] Copyright 2018, Wiley-VCH. b) Ultra-thin chips obtained by exfoliation from a silicon-on-insulator (SOI) substrate. Reproduced with permission.[125] Copyright 2008, AAAS. c) Flexible hybrid integration system. Reproduced with permission.[17] Copyright 2016, Wiley-VCH. d-e) Stretchable hybrid integration system. Reproduced with permission.[130] Copyright 2017, The Authors, published by Springer Nature.

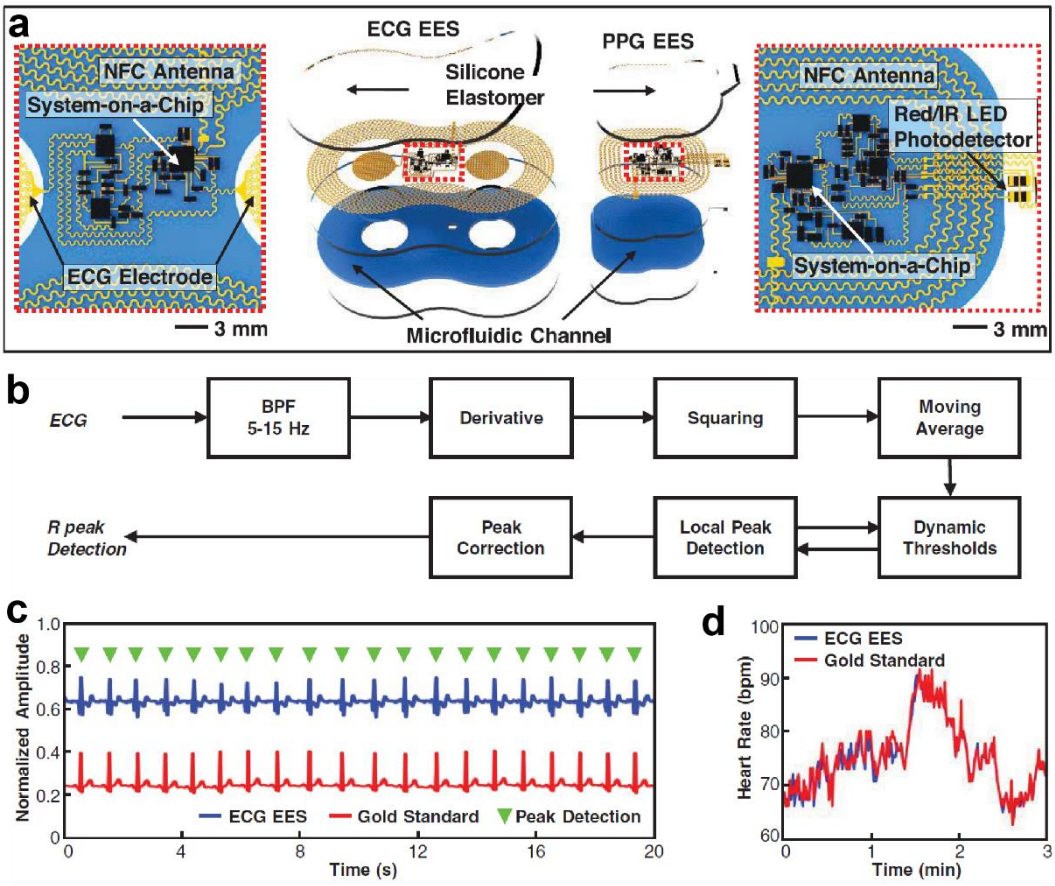

**Figure 4.** Hybrid integrated epidermal electronic system with the sensing and perception functionality. Reproduced with permission.[144] Copyright 2019, AAAS. a) Schematic of the hybrid integrated system. b) Block diagram of in-sensor processing ECG signals. c)-d) Comparison of raw ECG signals, peak detection, and extracted heart rate from the hybrid integrated system and a gold standard.

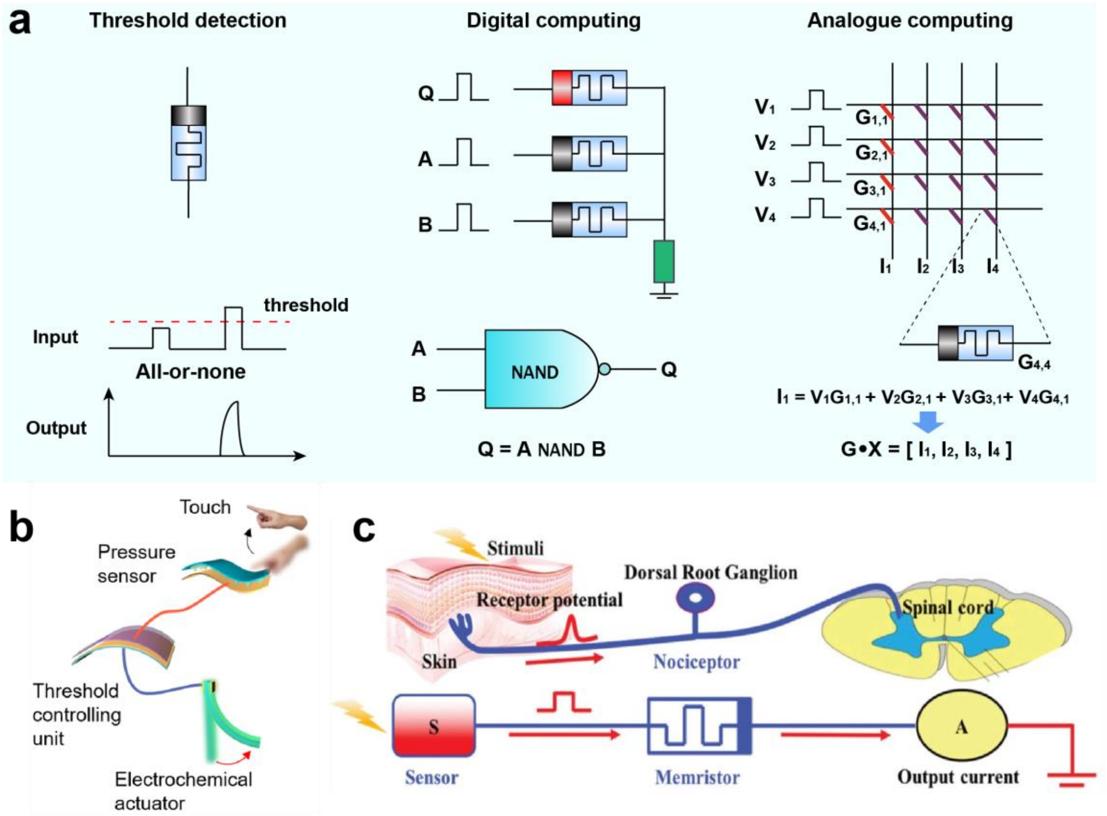

**Figure 5.** Flexible memristive devices for general-purpose computing. a) Schematic of the implementation of general-purpose computing using memristive device or array, including threshold detection, digital computing, and analogue computing. b) An artificial reflex arc system with artificial skin perception functionality. Reproduced with permission.[121] Copyright 2020, Wiley-VCH. c) Artificial nociceptor with artificial skin perception functionality. Reproduced with permission.[88] Copyright 2019, The Royal Society of Chemistry.

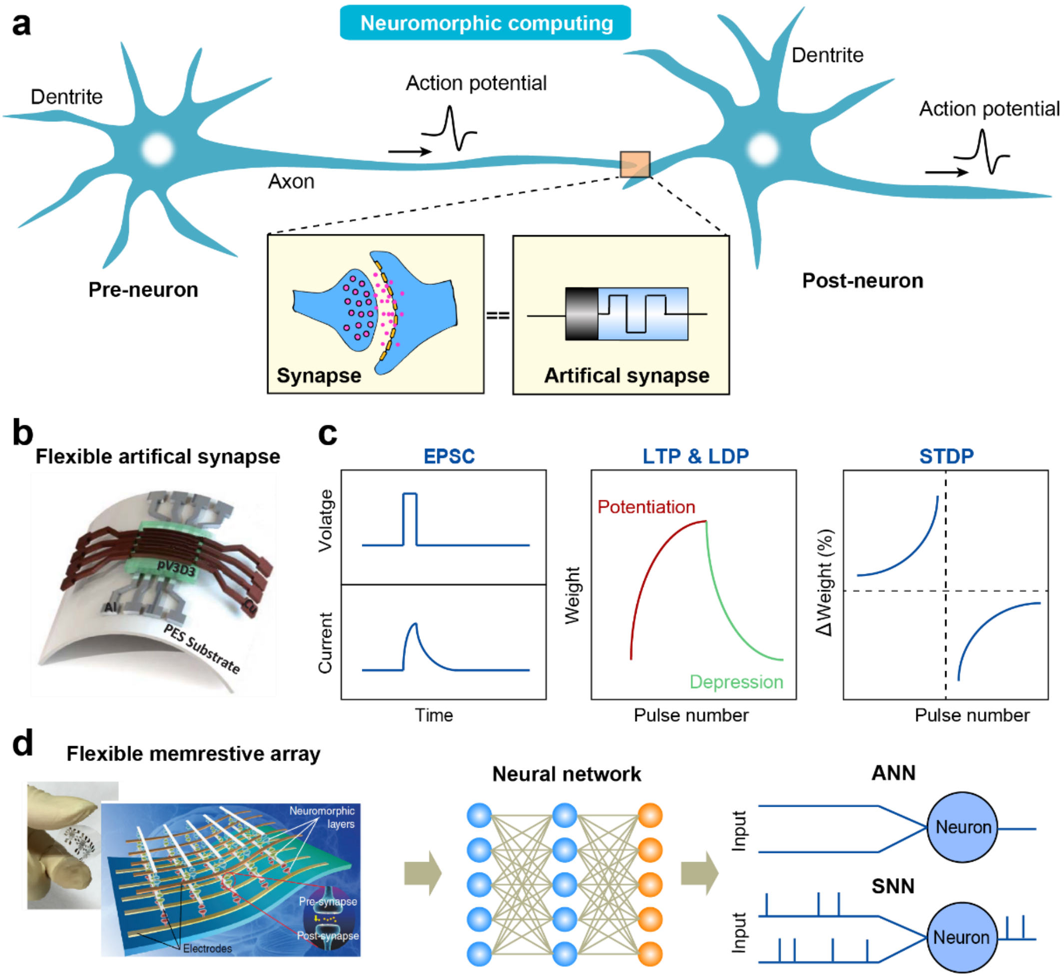

**Figure 6.** Flexible memristive devices for neuromorphic computing. a) Neuromorphic computing in the brain and schematic of the memristive device as an artificial synapse. b) Flexible memristive artificial synapse. Reproduced with permission.[28] Copyright 2019, American Chemical Society. c) Synaptic electrical behaviors emulated by memristive devices, including EPSC, LTP, LDP and STDP. d) Flexible memristive array for neuromorphic computing, including conventional ANN with static input coding and SNN with relative spike timing coding. Flexible memristive array image: Reproduced with permission.[24] Copyright 2017, The Authors, published by Springer Nature.

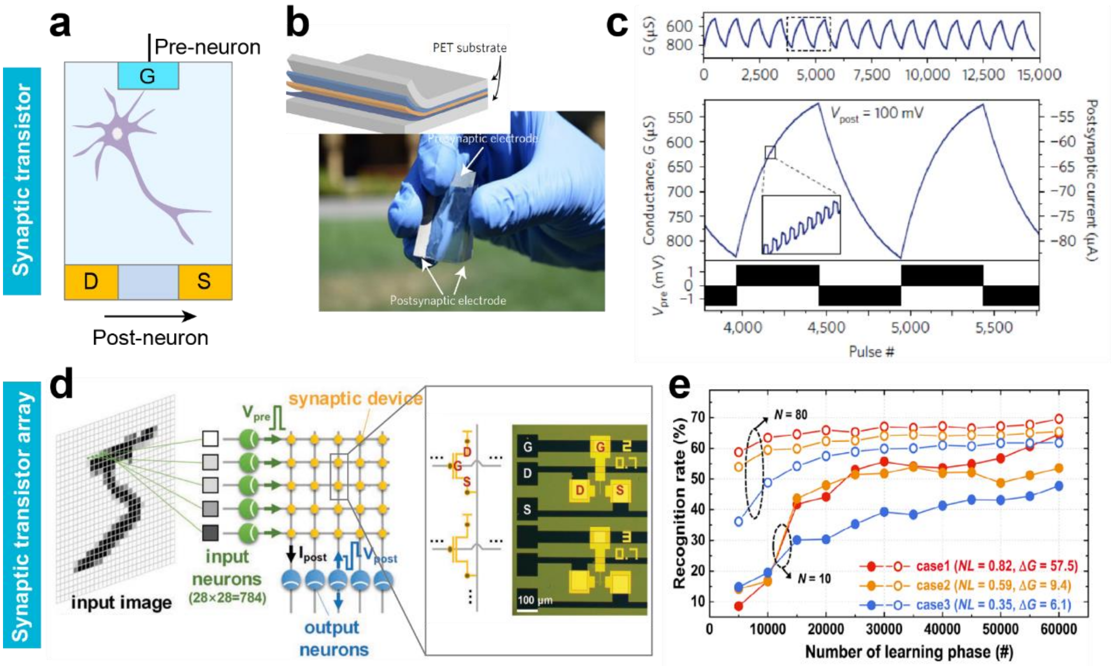

**Figure 7.** Flexible synaptic transistor for neuromorphic computing. a) Schematic of the transistor as an artificial synapse. b-c) Flexible organic electrochemical synaptic transistor with multiple discrete conductance states. Reproduced with permission.[29] Copyright 2017, Springer Nature. d) Array configuration of synaptic transistors for pattern recognition. Reproduced with permission.[217] Copyright 2018, Wiley-VCH. e) Handwritten digit recognition accuracy as a function of the number of learning phases based on the simulation of a flexible neuromorphic system. Reproduced with permission.[218] Copyright 2017, American Chemical Society.

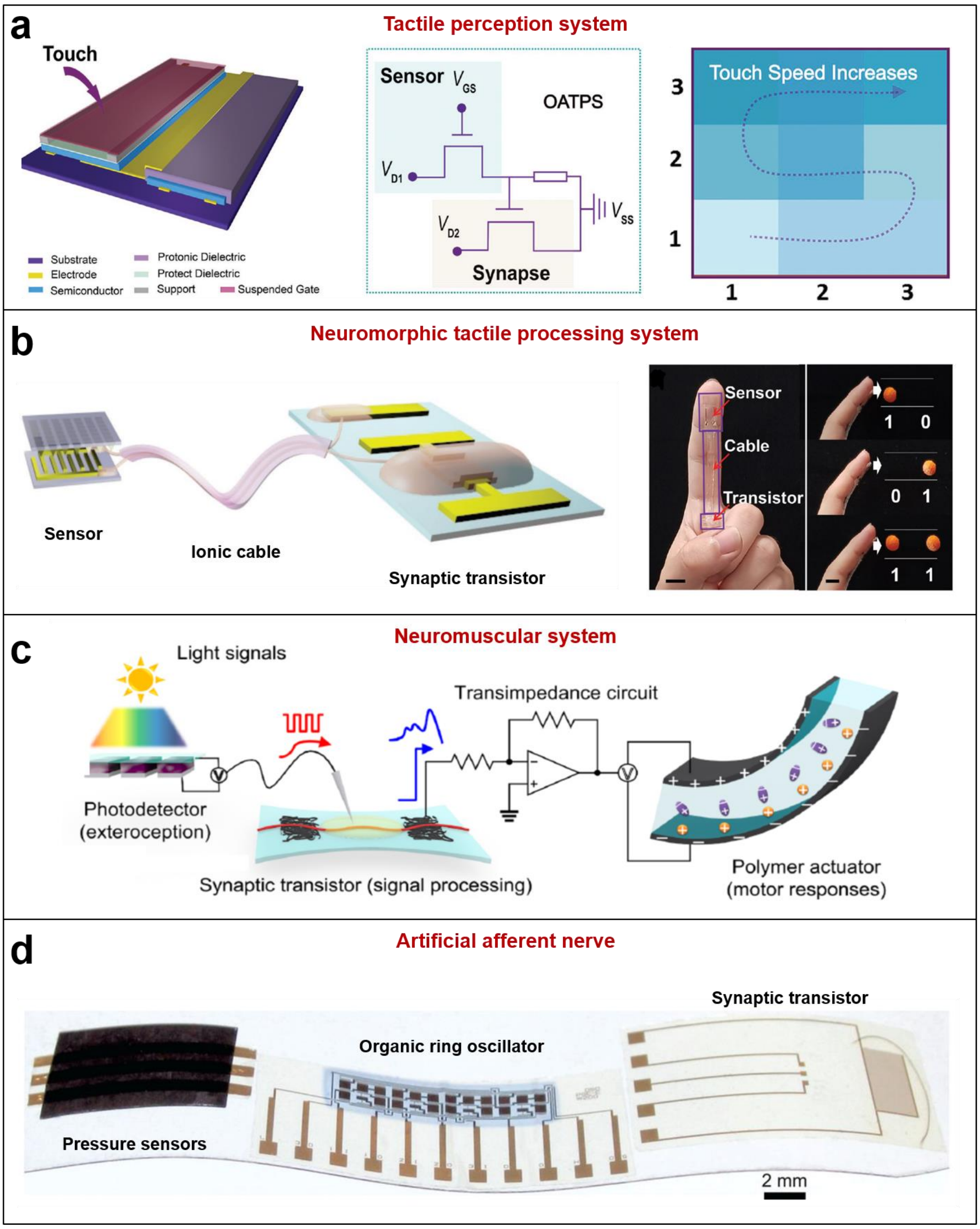

**Figure 8.** Flexible or stretchable artificial skin perception systems based on synaptic transistors. a) Flexible tactile perception system. Reproduced with permission.[219] Copyright 2017, Wiley-VCH. b) Flexible neuromorphic tactile processing system. Reproduced with permission.[220] Copyright 2018, Wiley-VCH. c) Stretchable neuromuscular system. Reproduced with permission.[221] Copyright 2018, The Authors, published by AAAS. d) Flexible artificial afferent nerve. Reproduced with permission.[223] Copyright 2018, AAAS.

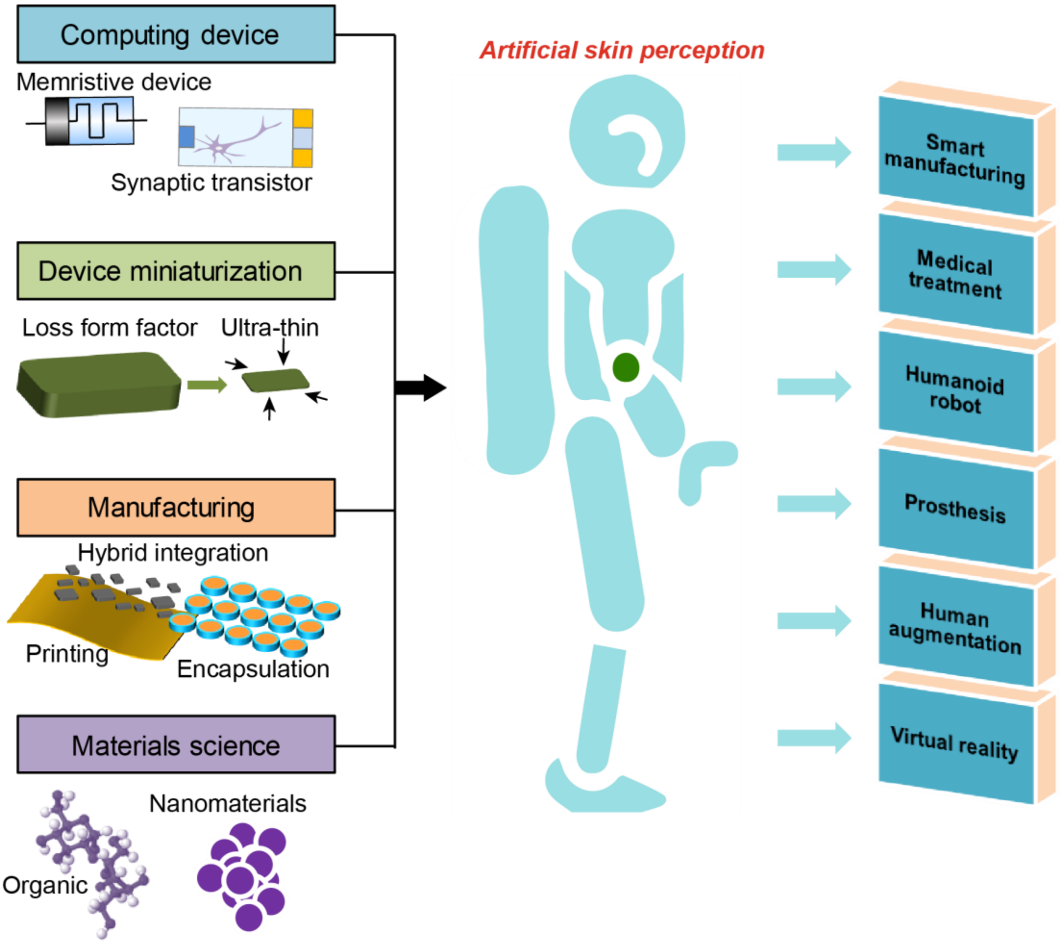

**Figure 9.** Perspectives of artificial skin perception. Materials science, manufacturing process, electronic device miniaturization, and new computing device will enable sensory information to process in a fast and energy-efficient way, potentially promoting the development of many domains.

**Table 1.** Specifications of the mechanoreceptors, including adaptation rate property, receptive field area, location, density, effective stimuli, and function.

| **Receptor** | **Meissner's Corpuscle** | **Pacinian Corpuscle** | **Merkel cell** | **Rufffini Endings** |
|---|---|---|---|---|
| Type | FA I | FA II | SA I | SA II |
| Adaptation rate property | fast | fast | slow | slow |
| Receptive field ($mm^2$) | 1-100 | 10-1000 | 2-100 | 10-500 |
| Frequency range (Hz) | 10-200 | 40-800 | 0.4-100 | 7 |
| Location | Dermis of glabrous skin | Deep layers of dermis in hairy and glabrous skin | Epidermis of glabrous skin | Dermis of hairy and glabrous skin |
| Receptors per $cm^2$ in the fingertip | 140 | 21 | 70 | 49 |
| Effective stimuli | Temporal changes in the skin deformation | Temporal changes in the skin deformation | Spatial deformation, sustained pressure, curvature, edge, corner | Sustained downward, pressure, lateral skin stretching, skin slip |
| Sensory function | Low frequency vibration, motion detection, grip control, tactile flow perception | High frequency vibration | Pattern or form detection, texture perception, tactile flow perception | Finger position, stable grasp, tangential force, motion direction |

**Table 2.** Recent progress in flexible and stretchable sensing devices via materials innovation and structural designs.

| Category | Target | Application |
|---|---|---|
| Mechanical sensing | Pressure | Force touch,[51-53] acoustic vibration,[54]<br>pulse wave,[55, 56] intraocular pressure,[57]<br>heart rate,[58] robotic skin,[59, 60]<br>tactile glove[61] |
| | Strain | Human motion,[63-65] pulse wave,[62]<br>acoustic vibration,[66] swallowing motion,[67]<br>tactile glove[68-70], soft robotic[71-73] |
| | Slip and Force Vector | Slip detection,[74-76] acoustic vibration[77],<br>robotic skin[75, 77] |
| Temperature sensing | Temperature | Skin temperature,[78-81] atmospheric temperature,[82]<br>artificial skin,[83] soft robotic[85]<br>photothermal therapy[86] |
| Nociceptive sensing | Artificial nociceptor (Sensor + memristor) | Pressure nociceptor[88], thermal nociceptor[89]<br>UV damage-sensing nociceptor[90]<br>humanoid robots[87-89, 91] |
| | Sensor system | Artificial muscle[92] |
| Proprioceptive sensing | Multimodal sensors or systems | Pneumatic artificial muscle,[93] prosthesis,[94, 100, 101]<br>object motion,[95-97] human-robot interactions,[98]<br>soft robotics[99] |
| Other-type sensing | Electrical signals | Electrophysiological signals, such as electromyography (EMG),[102-105]<br>electrocardiogram (ECG),[105-108]<br>electroencephalogram (EEG),[109, 110] |
| | Chemical signals | Glucose monitoring,[111, 112, 114] sweat analysis,[19]<br>biomarker,[113] |
| | Magnetic | Artificial magnetoreception[115], navigation[115, 116] |

**Artificial skin perception** that integrates the perception functionality into a flexible and stretchable sensing system could endow current electronic devices with much higher intelligence. The recent progress, challenges, and perspects of artificial skin perception are discussed in this Progress Report. This will offer some guidance and inspiration for the development of next-generation intelligent systems, especially soft robotics.

**Artificial skin**

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## Artificial skin perception

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